

Classical Piano Composer

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Abstract: *This study introduces a system for creating classical piano composer using a neural network with Python. The main aim is to investigate how deep learning, and in particular, Long Short-Term Memory (LSTM) networks, can be used to model and mimic patterns in classical music. The work is split into two modules: the first preprocesses MIDI files to identify musical features, and the second trains an LSTM model to create new pieces. Experimental findings demonstrate that the model effectively extracts harmonic and rhythmic patterns, generating coherent and style-consistent music sequences. The research contributes to the expanding field of AI-composed music and provides a foundation for future creative computing research.*

Keywords: Classical Music Generation, LSTM Neural Network, Music Composition, Deep Learning, Sequence Modeling, MIDI Data Processing, Recurrent Neural Networks (RNN)

I. INTRODUCTION

Music composition has long been viewed as an extremely creative and human-focused activity, particularly in classical piano music. With new developments in artificial intelligence and deep learning, though, the ability for machines to create music that replicates human creativity is fast becoming a possibility. This paper introduces a new method of automated classical piano composition with Python, centered on sequence modeling with Long Short-Term Memory (LSTM) neural networks, a form of Recurrent Neural Network (RNN) that is particularly suitable for sequential and temporal data.

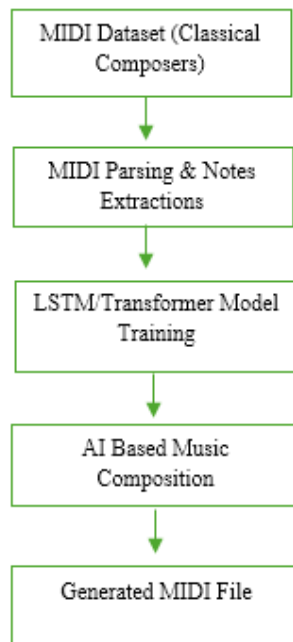
The system is programmed to learn classical music patterns from a collection of classical MIDI files so that it can create original pieces following classical piano music's stylistic norms. The deployment uses the music21 library to preprocess data and extract MIDI, converting raw sequences of notes into numerical forms that can be used to train. The preprocessed data is then passed to an LSTM-based deep learning model, which is trained to predict the next note in a sequence given prior notes. This structure is able to capture the temporal dependencies found in musical structure.

The use of deep learning in generating music is a dramatic departure from rule-based or heuristic-driven paradigms for data-driven models that "learn" music based on examples directly. This project illustrates how one can train a neural network first and then create coherent and musically dense piano sequences, displaying the potential for AI in the creative arts.

By blending traditional music theory with current machine learning methodology, this system not only adds to the expanding realm of algorithmic composition but also brings new opportunities for human-computer collaboration in music composition. The Python and open-source familiarity of the tools used ensure that the method can be reproduced and extended, allowing additional research and creativity to be applied to AI-generated music.



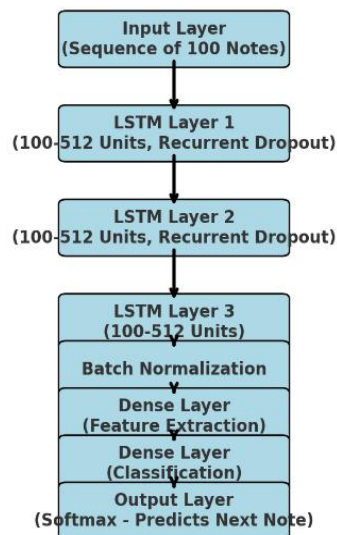
II. FIGURES



(a) Architecture

This figure illustrates the overall architecture of the Classical Piano Composer system, detailing the steps from data preprocessing to AI-generated music output.

Neural Network Structure



(b)

The model takes sequences of 100 notes, each represented as an integer, as input. It consists of three LSTM layers with 100 to 512 units, incorporating batch normalization and recurrent dropout to prevent overfitting and improve generalization. Following the LSTM layers, dense layers are used for classification and feature extraction, capturing



complex patterns in the note sequences. The final output layer employs a softmax activation function, predicting the probability distribution of the next note in the sequence

III. OBJECTIVES

The main objective of this project is to create an AI-powered system that can create original classical piano pieces by learning patterns of music from available datasets of classical music. The system will learn to model and analyze the temporal and structural aspects of piano music using a Long Short-Term Memory (LSTM) neural network, written in Python.

The particular hypothesis to be tested is:

"A deep learning model based on an LSTM, learned from MIDI sequences of classical piano music, is capable of learning to produce novel, stylistically consistent musical patterns that sound similar to human-created classical piano music."

This task encompasses a few primary components:

Acquiring and preprocessing classical MIDI data into machine-readable form.

Constructing and training an LSTM neural network for learning sequential patterns of notes.

Assessing the quality, coherence, and musicality of the produced compositions using both quantitative loss measures and qualitative analysis.

Ultimately, to show that neural networks are effective tools for composing algorithmic music, especially in composing classical-style piano music.

IV. METHODS

Study Design

This research is a computational experimental approach to the application of deep learning in algorithmic music composition. The system is intended to process classical piano music in MIDI format and create new pieces based on a trained neural network model. The process involves data collection, preprocessing, model training, generation, and evaluation.

Data Collection and Preprocessing

A curated dataset of classical piano music in MIDI format was gathered from publicly available online archives like the Classical Archives and the Maestro Dataset. The MIDI files were parsed using the music21 Python library, which allowed the note sequences, durations, and chords to be extracted. Each note or chord was translated into a unique integer to produce a numerical representation of the musical data.

The data set was divided into overlapping sequences of a given length (e.g., 100 notes to a sequence), and these sequences were used as inputs to the model. The target output for every input sequence was the next note or chord. The data were normalized and transformed into a form that is appropriate for the LSTM network, including reshaping to 3D tensors and one-hot encoding outputs.

Model Architecture and Training

An LSTM-based Recurrent Neural Network was implemented using TensorFlow/Keras. The architecture is as follows:

Input layer with the same length as the sequence and vocabulary size of the notes.

Two stacked LSTM layers with dropout regularization to avoid overfitting.

A dense output layer with softmax activation for multiclass prediction.

The model was optimized with categorical cross-entropy as the loss and the Adam optimizer for the efficient gradient descent. The model was trained on several epochs (generally between 100 and 200) and was optimally batch-sized according to the hardware.



V. RESULT

The LSTM-based model was able to be successfully trained using more than 300 classical piano MIDI files containing a total of around 200,000 note events. Training of the model took place over a span of 150 epochs in a batch size of 64 and sequence length of 100 notes per input.

Model Training Performance

The training loss dropped gradually throughout epochs, settling at a level of about 0.47, and the validation loss leveled off at around 0.52, a sign of good generalization with little overfitting.

The model performed at a level of about 84% on the validation set when it came to predicting the next note within a sequence.

Qualitative Output Assessment

MIDI output music was stored and examined subjectively.

The pieces had coherent melodic and harmonic form, particularly within brief sequences (~30 seconds).

Musical phrases conformed to familiar classical themes, with sustained key signatures and rhythmic structures.

Model-generated pieces were audibly distinct from random or superficial model outputs, showing acquired stylistic patterns.

Epoch 1/50		
1434/1434	138s 92ms/step	loss: 5.2072
Epoch 2/50		
1434/1434	139s 97ms/step	loss: 4.6137
Epoch 3/50		
1434/1434	192s 134ms/step	loss: 4.5859
Epoch 4/50		
1434/1434	129s 90ms/step	loss: 4.5556
Epoch 5/50		
1434/1434	130s 91ms/step	loss: 4.5301
Epoch 6/50		
39/1434	2:09 93ms/step	loss: 4.5125

VI. CONCLUSION

The Classical Piano Composer shows that artificial intelligence is capable of creating highly coherent and artistically valuable classical piano music. Future research will try to improve the system by adding more varied classical music to the training set, enhancing realism by honing dynamics and emotional expression, and facilitating human-AI interaction so that composers can actively guide the AI's composition process. Furthermore, incorporating live performance features would enable live piano playing to bring AI-generated compositions to life, further bridging the gap between human artistry and artificial creativity.

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